



# Inferring Convolutional Neural Networks' accuracy from its architectural characterizations

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# Outline

## I. MINERvA experiment

- a. Neutrinos and MINERvA detector
- b. Vertex finding and hadron multiplicity problem

## II. Deep Learning

- a. Deep Neural Networks
- b. Convolutional Neural Networks (CNNs)
- c. CNN's design difficulties

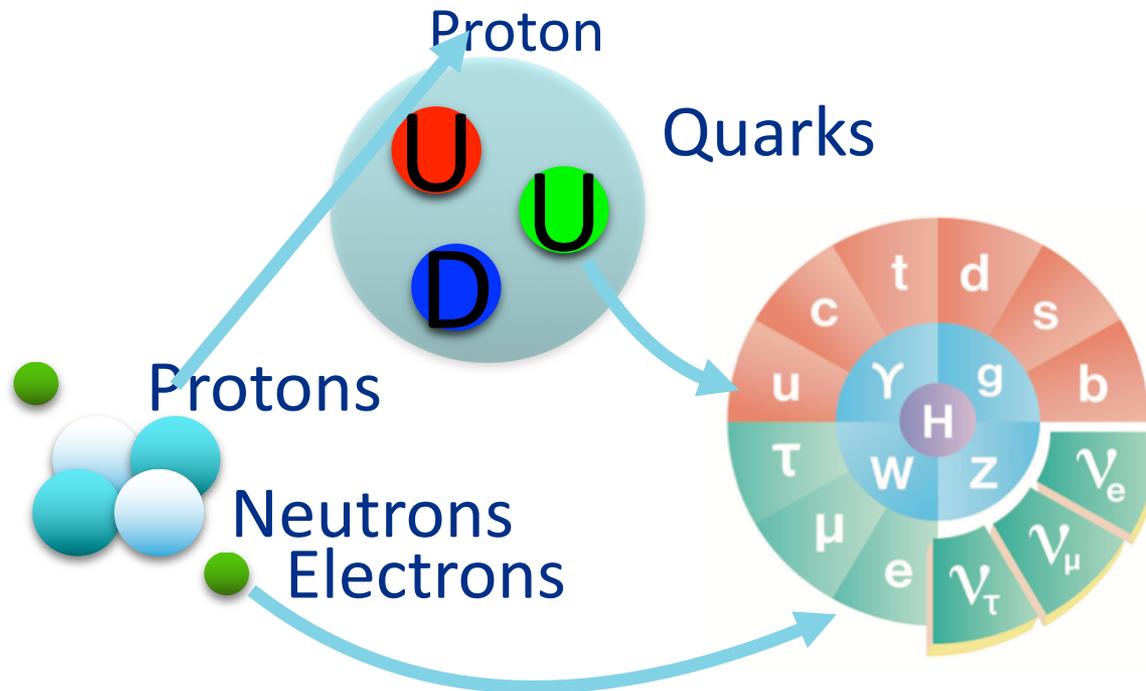
## III. Inferring CNNs' accuracy before training time

- a. Architectural characterizations
- b. Predicting CNNs' accuracy based on characterizations – why is it useful?

## IV. Summary & Outlook

# Neutrinos

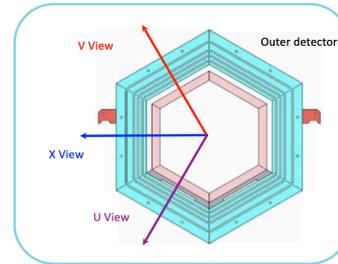
- Neutrinos are **fundamental**.
- They are **electrically neutral "partners"** of the familiar charged leptons (e.g., electrons).
- They are **very light**,
- **They very rarely interact** with other particles



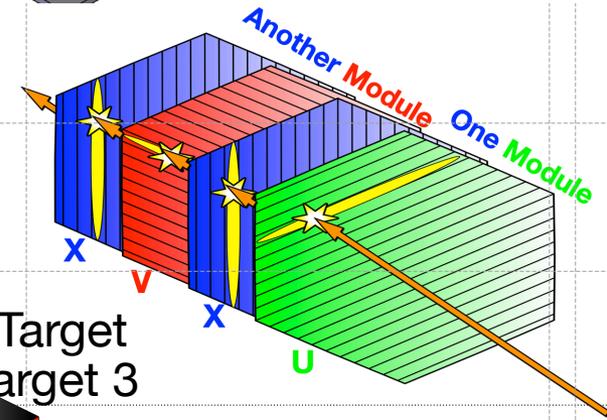
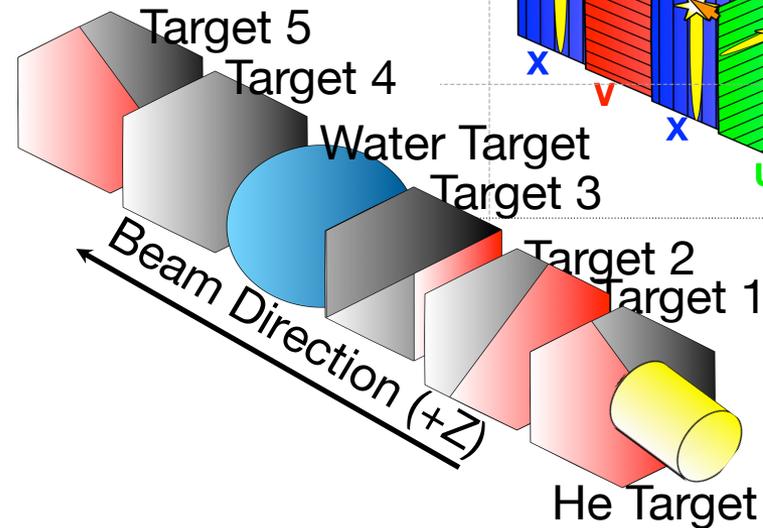
# MINERvA



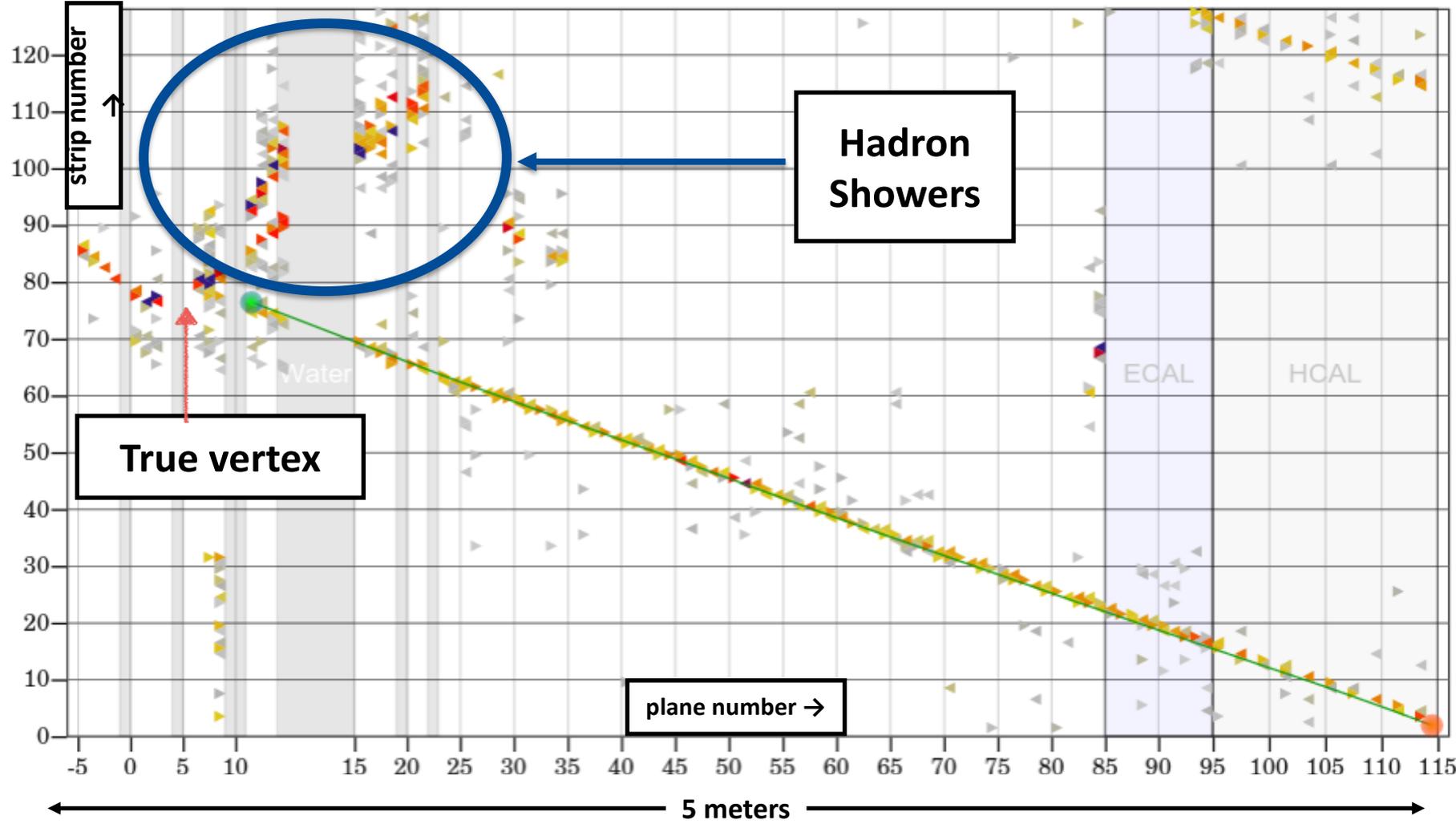
- Nuclear effects with a variety of target materials ranging from Helium to Lead.



- Fine-grained resolution for excellent kinematic measurements.

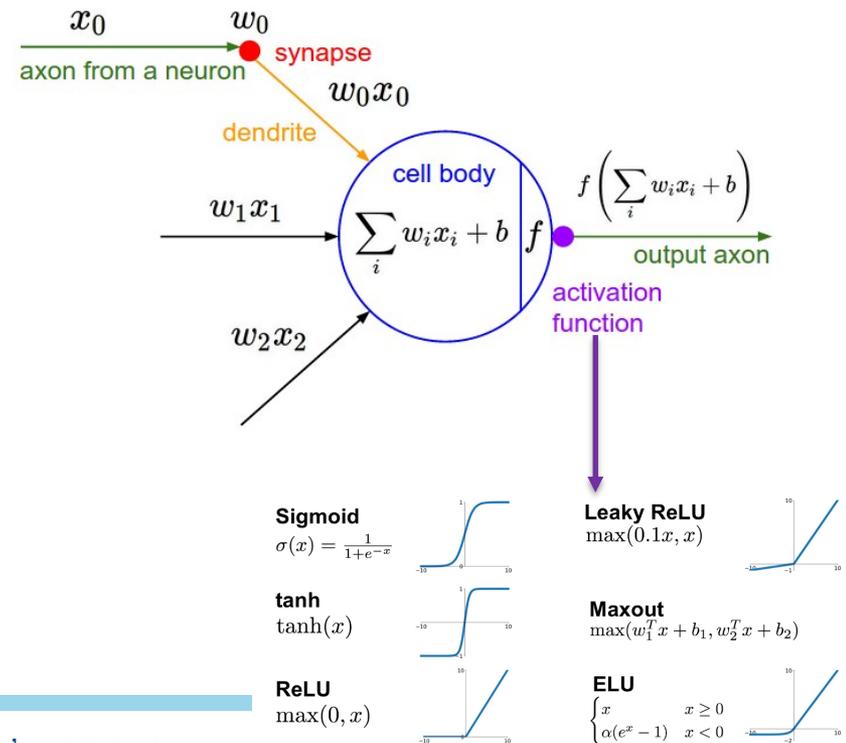
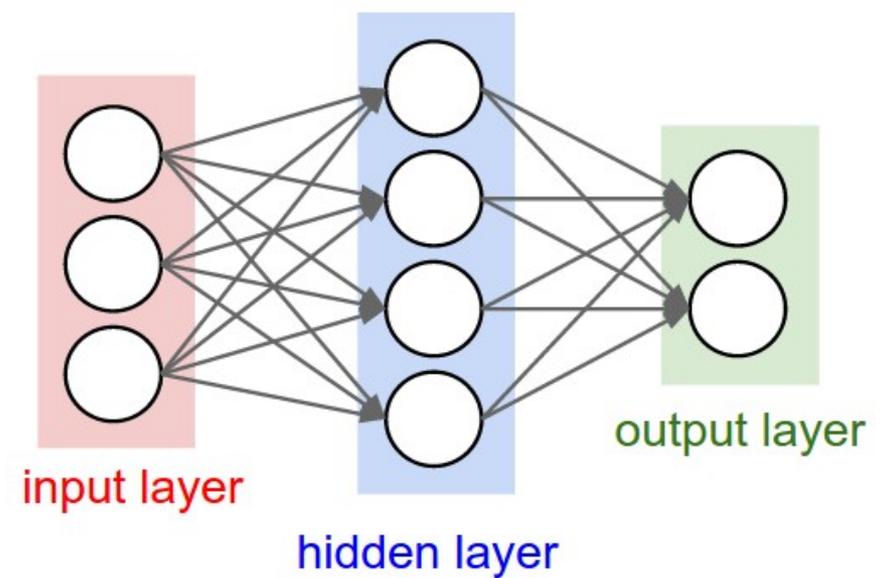


# Vertex Finding and Hadron Multiplicity problem



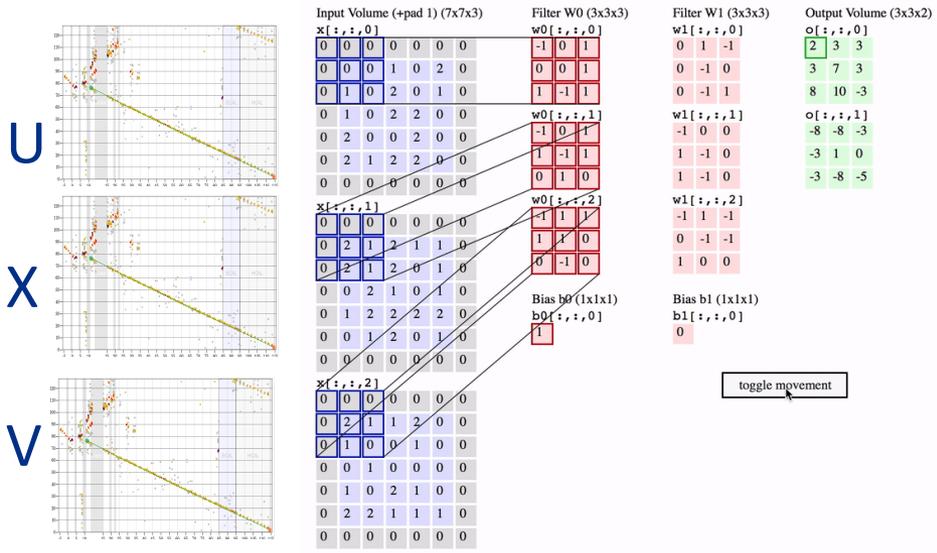
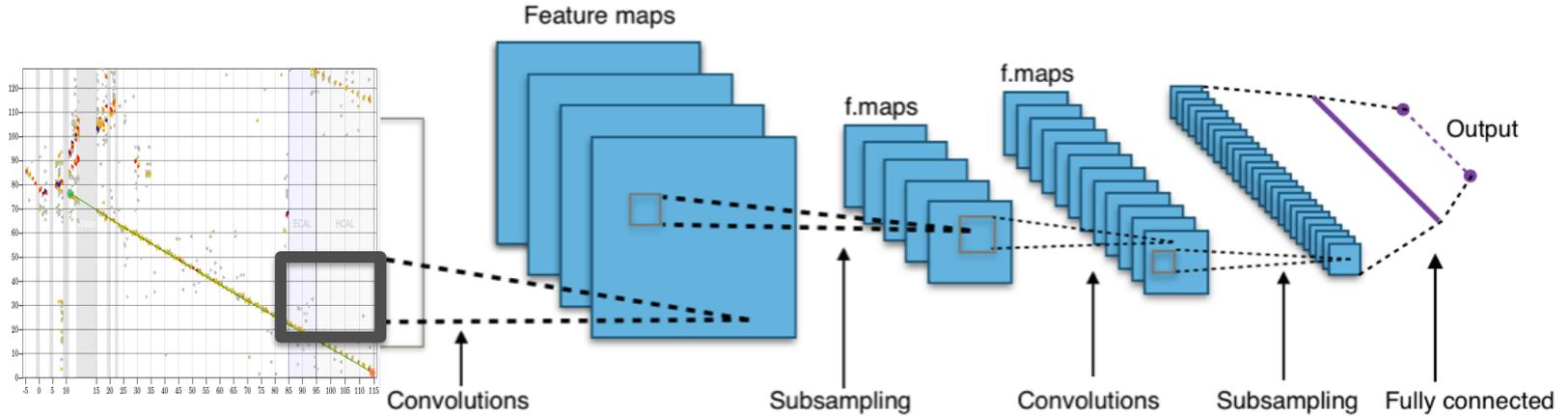
# Deep Neural Networks

- Fully-connected architecture
- Each **input** multiplied by a **weight**.
- **Weighted values** are summed, **Bias** is added.
- Non-linear **activation function** is applied
- Trained by varying the **parameters** to minimize a loss function (quantifies how many mistakes the network makes)



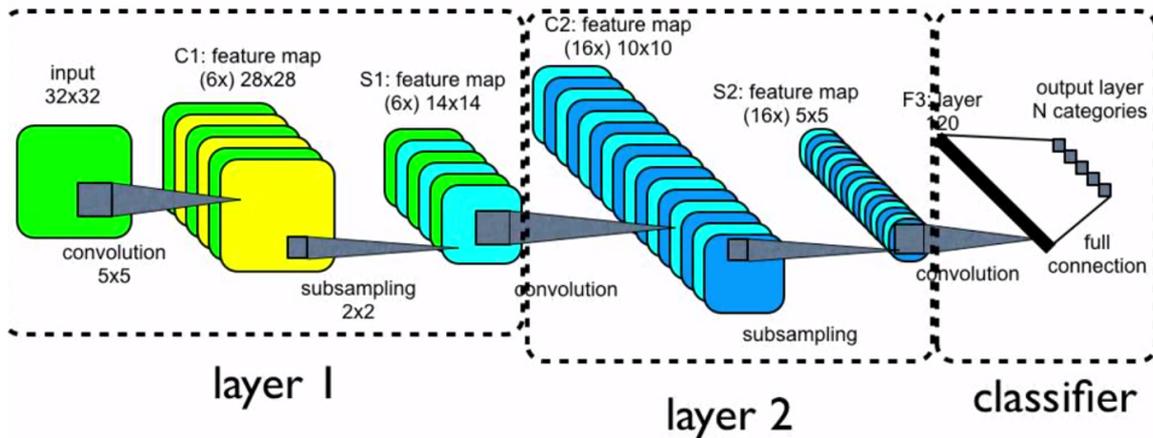
# Convolutional Neural Networks (CNNs)

- Similar concept to Deep Neural Networks, but highly effective for **image inputs**, and modern neutrino detectors are **imaging detectors**.



# Difficulty

- There is no universal CNN design for every tasks.
- And designing an appropriate structure/architecture of CNN takes a lot of time and effort even for the experts.
- There is no systematic way to design CNNs: mainly rely on human intuition and random/grid search.
- Computationally expensive to train a CNN model.

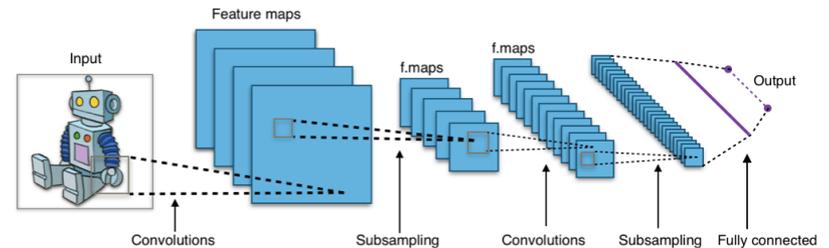


# Objectives

- I. Propose a **systematic language** to characterize CNN's architecture, and demonstrate that they can be **predictive** of a CNN's accuracy.
  
- II. Suggest **architectural changes** to CNNs for different physics tasks (vertex finding and hadron multiplicity)

Examples of architectural attributes we extracted (32 in total):

- Number of convolutional layers.
- Number of rectified linear unit (ReLU) activated convolutional layers.
- Average depth



# Method

Interpret the models

Important architecture  
of CNN for physics task

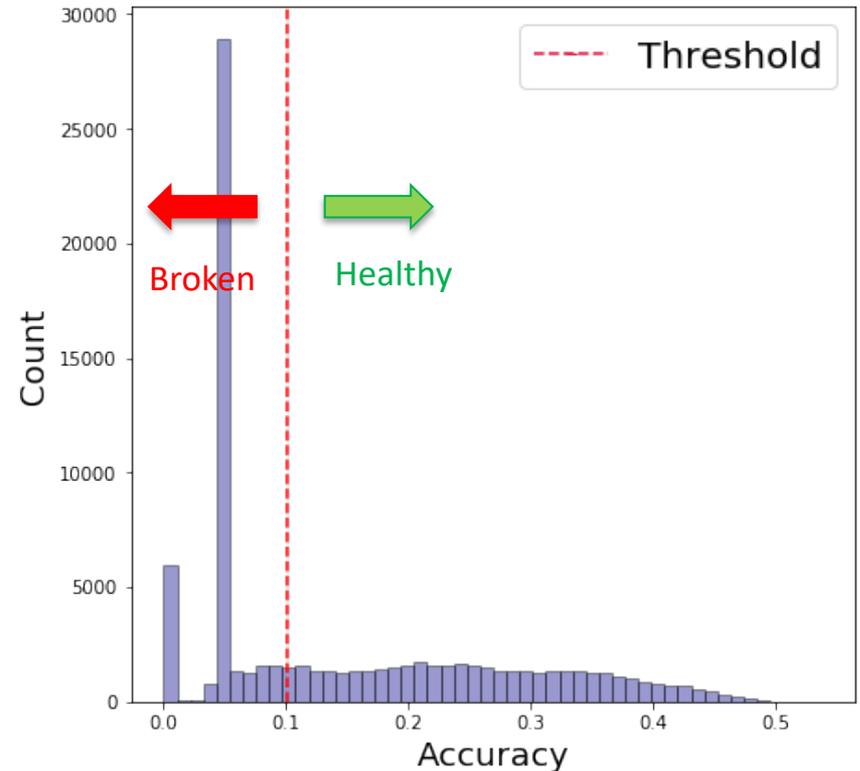
Machine  
Learning models  
(classification  
and regression)

Architectural  
characterizations

CNN performance (accuracy)

# Classification

- Divide data set into *broken* and *healthy* networks.
- Use **Random Forest** and **Extremely Randomized Tree** to predict each CNN's class.

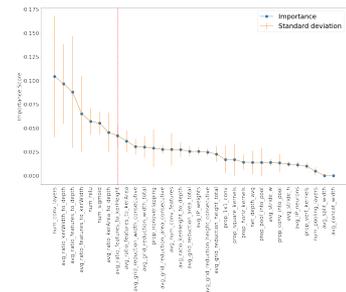
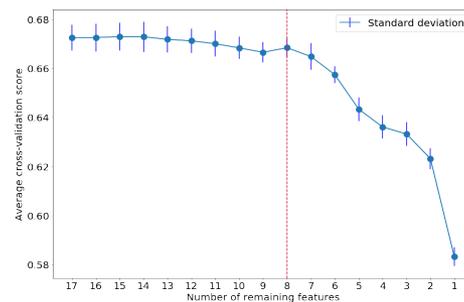


# Classification results

- Machine Learning models perform **significantly better** than random guessing (50% when there is no class overflow):

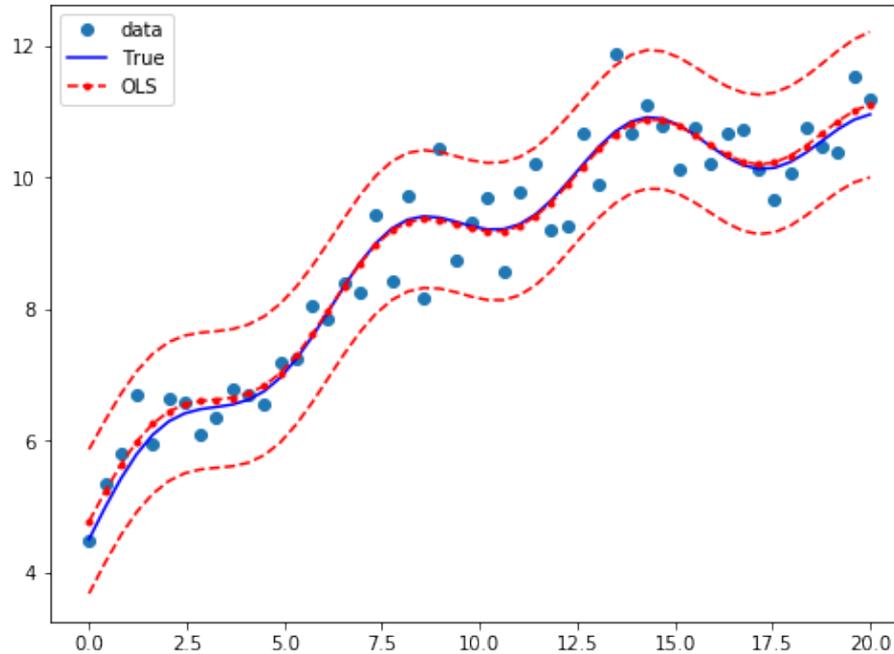
Model	Average 5-fold cross-validation scores	Accuracy on test set
Random Forest	70.3 $\pm$ 0.006 %	70.6 %
Extremely Randomized Tree	70.2 $\pm$ 0.003 %	70.5 %

- Were also able to extract important features to suggest architectural changes to CNNs. **More details in paper.**



# Regression on just healthy networks

- Fitted a non-linear Ordinary Least Square model on just the *healthy* networks.



# Regression results

- Models fitted on two populations of vertex finding CNNs:

Population	$R^2$ of OLS	Number of <i>Healthy CNNs</i>
First	0.426	49276
Second	0.295	21415
Combined	0.961	70691

- Limitations:** Still not enough parameters to characterize the detailed relationship between CNN's architecture and its performance. ► Planning to extend attribute set in the future.

# Outlook & Summary

- Proposed a systematic language to characterize convolutional neural networks architecture.
- Successfully demonstrated that we can use those parameters to predict whether a network is “good”.
- There are limitations to predict the exact accuracy, but initial results are promising. Extension of the attributes set might help in the future.
- One of the early studies about relationship between CNN’s architecture and its performance.
- **More details in our up-coming paper.**

# Acknowledgements

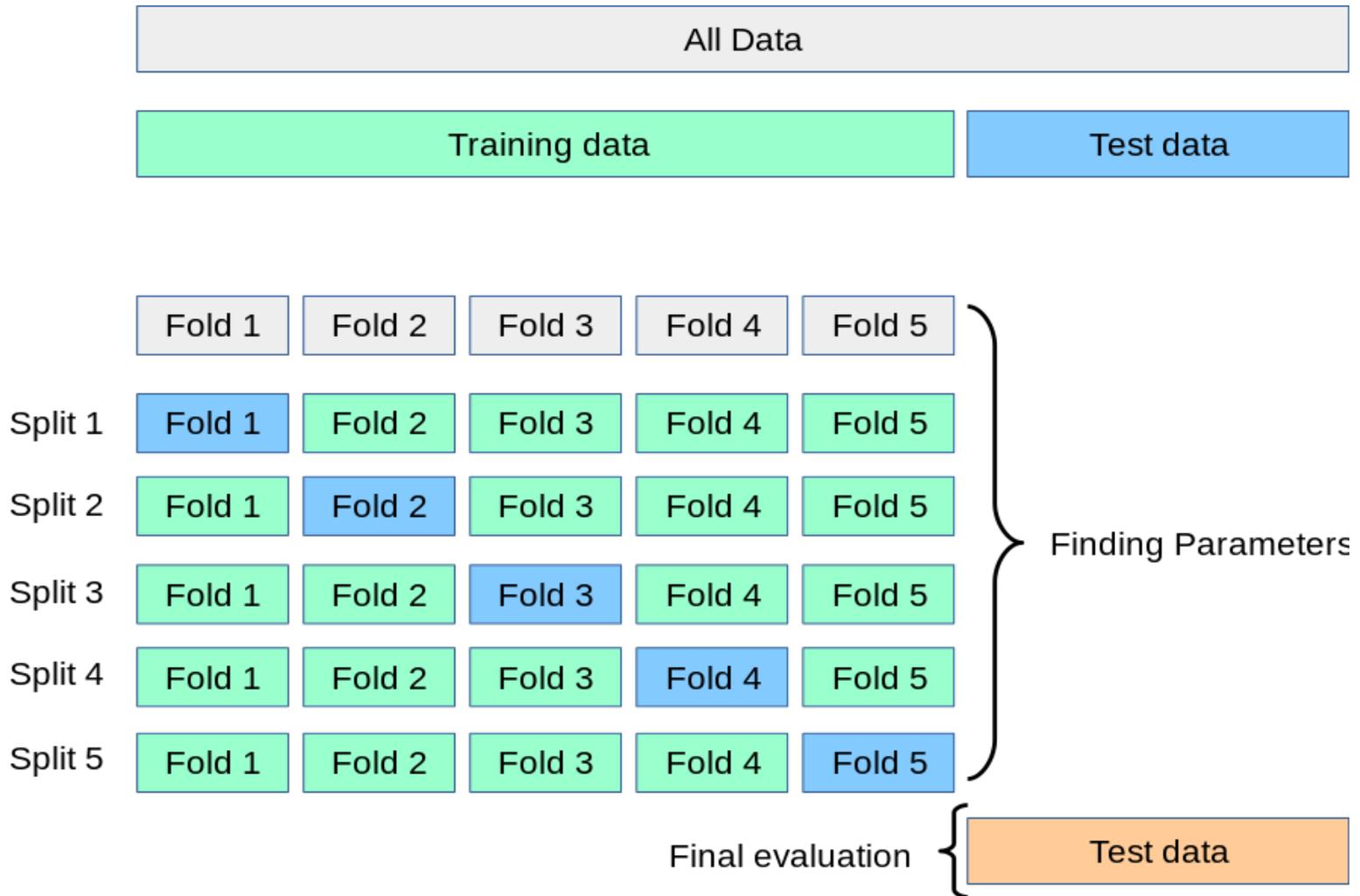
- Special thanks to my supervisor, Dr. Gabriel N. Perdue.
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  - Laura Fields
  - Sandra Charles
  - Judy Nunez
  - Alexander Martinez
  - Raul Campos
  - Matthew Alvarez

# References

- Neural networks and Convolutional Networks visualization: [Source](#)
- Random Forest: [Source](#)

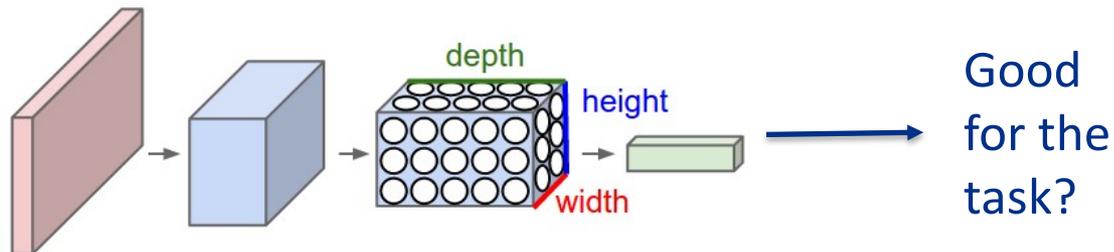
# Back-ups

# K-folds cross validation



# Architectural characterizations of CNNs

- Different deep learning problems require different network architecture.
- However, selecting an appropriate architecture for CNNs is usually done by human intuition or random search
- If we have a way to uniformly characterize a network architecture, then it would be particularly useful.



# Random Forest and Extremely Randomized Tree

